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Authors
Kalaycı, K
Serra-Garcia, M

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Complexity and Biases*

Kenan Kalaycı†
University of Queensland

Marta Serra-Garcia‡
UCSD

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Abstract

We examine experimentally how complexity affects decision-making, when individuals choose among different products with varying benefits and costs. We find that complexity in costs leads to choosing a high-benefit product, with high costs and overall lower payoffs. In contrast, when complexity is in the benefits of the product, we cannot reject the hypothesis of random mistakes. We also examine the role of heterogeneous complexity. We find that individuals still (mistakenly) choose the high-benefit but costly product, even if cheaper and simple products are available. Our results suggest that salience is a main driver of choices under different forms of complexity.

JEL codes: C91, D03, D14, G02

Keywords: Complexity, Mistakes, Credit Choice, Experiment, Salience

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†E-mail: k.kalayci@uq.edu.au. Address: University of Queensland, School of Economics, Colin Clark Building (39), St Lucia, Brisbane, Qld 4072, Australia.

‡Corresponding author. E-mail: mserragarcia@ucsd.edu. Address: UCSD, Rady School of Management, 9500 Gilman Dr., La Jolla, CA 92093.

1 Introduction

Complexity is present in many decision processes, yet we know very little about *how* it affects choices. While it has been long recognized that individuals have limited cognitive resources that may lead to mistakes in decision-making (Simon, 1957), the question remains: what kind of mistakes does complexity cause? What guides individuals' choices in complex environments?

One of many complex environments is financial decision–making. Consumer financial choices are often overwhelmingly complex (Campbell, 2006). Even small financial transactions, such as consumer loans, can be complicated and are usually characterized by several types of fees and bonuses that differ across providers. Not surprisingly, the complexity of products in financial markets has generated substantial concern among policy makers (e.g., OECD, 2005). Such concerns about complexity are especially warranted for credit products, as mistakes can lead individuals into harmful debt spirals (Lusardi and Tufano, 2009).

Despite the concern of policy makers, the standard approach to decision making does not take complexity into account. Recent behavioral models of decision-making, however, suggest different effects of complexity. One approach is to assume that complexity increases the number of random mistakes. Carlin (2009) uses such an approach to model complexity and competition in financial markets, showing that as competition increases, complexity may increase as well. On the other hand, Gabaix and Laibson (2006), among others, suggest that when products have immediate benefits but future and complex costs, complexity may lead to more myopic choices, i.e. based solely on benefits. More recently, models of salience (Bordalo et al., 2013, Köszegi and Szeidl, 2013), posit that individuals tend to focus on the most salient attributes, often simpler ones, when choosing among products.[1]

Our experiment explores how decision–making changes with different forms of arithmetic complexity. We examine decision making among three products, each of which has a benefit level and offers three different costs. In particular, there is a high-benefit product, with high costs; a medium-benefit product, with lower costs and the highest net payoff; and a low-benefit product, again with low costs, but lower net payoff than the medium-benefit product. Individuals first choose a product, having all information available, and then choose among the costs available. Such stylized environment aims to capture features of some credit decisions, e.g. choosing among loan offers or among credit cards, where credit amounts are made available and may be repaid in different ways,

[1] Another related theory of complexity and inattention is, e.g., thinking aversion (Ortoleva, 2011).

subject to different fees.

We conduct two types of experimental sessions, A sessions and B sessions. In A sessions all products have either complex benefits or costs, or are simple in both dimensions. When costs are complex, the fees of a product are presented as the sum of a standard fee, a percentage fee on benefit and a bonus. When they are simple, they are presented as a single number. Throughout the experiment, we vary the labels and position on the screen of each product.

When all products are simple in both benefits and costs, most subjects choose the medium-benefit product (84%). Interestingly, there is a small bias toward the high-benefit product (11%), with the low-benefit product getting chosen in less than 6% of the time. When complexity in benefits is introduced, we find that mistakes increase relative to a simple environment, but we cannot reject that the increase in choices towards the high-benefit product - now chosen 23% of the time - is significantly different to that towards the low-benefit product - now chosen 10% of the time. In contrast, when costs are complex, the increase in mistakes towards the high-benefit product is significantly larger than that towards the low-benefit product. The high-benefit product is now chosen 39% of the time, while the low-benefit product is chosen 15% of the time. Hence, the type of complexity has significantly different effects on the type of mistakes made by the subjects in the experiment.

In B sessions we examine whether the effect of complexity depends on the number of complex products available. In this case, we compare situations where all products are simple and all products have complex costs, to a situation where only the high-benefit product has complex costs and a situation where both the high-benefit and the low-benefit product have complex costs. If all other options are presented in simple terms, is the high-benefit option, with complex and high costs, still chosen?

As in A sessions, when all products are simple, a majority of subjects choose the medium-benefit product (92%). The high-benefit product is chosen 4% of the time and the low-benefit product is chosen 4% of the time. Consistent with the results in A sessions, when all costs are complex, the increase in choices of the high-benefit product (chosen 35% of the time) is significantly higher than the increase in choices of the low-benefit product (chosen 19% of the time). When we introduce a situation in which the high-benefit product is the only complex product, mistakes decrease, but the tendency to choose the high-benefit product remains strong. Subjects choose the high-benefit product with complex costs in 22% of the cases, even if the medium-benefit and low-benefit product have simple costs. If the low-benefit product also presents complex costs, the frequency with which the high-benefit product is chosen does not significantly change.

Taken together, our results suggest that complexity in costs increases the focus on the simpler dimension, benefits, leading to the choice of the high-benefit product, with high costs. In contrast, complexity in benefits does not lead to mistakes that are significantly biased towards the high-benefit or the low-benefit product. Our results suggest that when benefits are complex and cost simple, individuals can easily identify the lowest cost of each product and then choose randomly among each product.

How can these choices in complex environments be explained? Behavior is not consistent with complexity always leading to random mistakes (due to the strong bias when costs are complex). We explore two alternative explanations: salience (Bordalo et al., 2013; Köszegi and Szeidl, 2013) and narrow bracketing (Read et al., 1999). A key difference between these explanations is timing. Narrow bracketing is more likely to occur when decisions are made in two stages, while the salience of products does not depend on how the decision process is structured. We conduct an additional treatment in which all choices are made in one stage. Our results indicate that timing has no significant effect on choices, suggesting that salience is the main driver of choices in complex environments.

Our paper is related to Finkelstein (2009) who find that paying road tolls electronically (rather than in cash) reduces the salience of the cost of the toll and hence leads to increased consumption. Relatedly, Chetty et al. (2009) find that consumers underreact to sales taxes that are not included in the posted price and Brown et al. (2010) find that shrouding shipping costs on eBay auctions leads to higher revenues for those items. Although the behavioral mechanism that leads to mistakes, salience, in these papers is similar to our paper, the underlying cause of reduced salience is hidden information in the above-mentioned studies while it is arithmetical complexity of costs (or benefits) in our case. This difference in the source of reduced salience leads to important differences in policy implications. While the remedy to hidden information is disclosure of more information the remedy for complexity is disclosure of less but simpler information. Another novelty of our paper is that we study products that have heterogeneous levels of complexity (in B sessions) while previous studies compare decisions made in simple and complex choice environments.

Our results are in line with recent findings by Bertrand and Morse (2011), who conduct a field experiment on pay-day borrowing.[2] In two related experimental studies, Beshears et al. (2010)

[2] Relatedly Ausubel (1999) finds that recipients of credit card solicitations overrespond to the introductory interest rate relative to the duration of the introductory offer and to the post introductory interest rate.

and Choi et al. (2010) explore the effect of simplified disclosure and “cheat sheets” in mutual fund choices. Their findings suggest that offering clear information about fees of different mutual funds may only be of limited help to consumers. One potential explanation for their result compared to ours is that mutual fund investments are still somewhat complex, due to their uncertain future returns. In our experiment, in the absence of risk, when all products are simple, subjects almost always make the correct choices.[3]

Our experimental findings are also related to a growing literature on bounded rationality and industrial organization (Spiegler, 2011). Our results suggest that complex products may potentially exist even in competitive environments. While our study examines only one-sided changes in complexity, abstracting from the effect of competition among suppliers, recent studies suggest that producers may indeed strategically use complexity in product markets (Kalaycı and Potters, 2011, Kalaycı, 2015).[4]

2 Experimental Design

The experiment is an individual choice task, where subjects make choices among different products. Subjects make decisions in two stages. In the first stage, subjects choose between three products. In the second stage, subjects choose among the available costs for the product they chose in the first stage. Each product has three possible costs, which are observable to the subject in the first stage. The payoff of each subject is the product benefit minus the cost she chooses.

$$\text{Payoff} = \text{Benefit of the Product - Cost of the Product}$$

The parameters, shown in Table 1, were chosen such that the first product, called the ”High” option, offers the highest benefit but has high costs. Taking this option’s benefit and subtracting the lowest cost, yields a maximum payoff of 30. In contrast, the second option, called the ”Medium” option, has the second highest benefit but lower costs. It thus yields the highest maximum payoff, 33. The third option, called ”Low”, has the lowest benefit and the lowest possible cost. However, the lower benefit implies that the maximum payoff that can be obtained by choosing the Low option is 30, the same as the High option. We chose these particular parameters to make sure High and Low offers the same potential maximum payoff while Medium offers a reasonable 10% premium

[3]Other experimental studies that focus on complexity are, among others, Abeler and Jäger (2013), who examine the interaction between tax complexity and effort choices, and Sitzia et al. (2012), who examine complexity in gas and electric tariffs.

[4]See also Sitzia and Zizzo (2011).

compared to the other two options. We will describe a subject's choice as a mistake if she does not choose the Medium option. This is justified by the fact that options are otherwise equal and, if choices are simple, an ample majority of the subjects indeed choose the Medium option.[5]

Option	Benefit	Costs	Maximum payoff
High	73	49 45 43	30
Medium	67	45 43 34	33
Low	61	43 34 31	30

Table 1: Base numbers

We frame choices among products as loan choices, providing subjects a context to their individual decisions. This provides a more natural environment, where subjects may be aware of the dangers of such products and hence provides a potentially lower bound for mistakes (for a further discussion see Harrison and List, 2004). In the experiment, the benefit is labeled as Value, the options as Loan A, Loan B and Loan C, and costs as Repayment X, Repayment Y and Repayment Z for each loan. The assignment of the High, Medium and Low benefit loans to the labels Loans A, B, C and the costs to Repayments X, Y, Z are randomized by the computer and are the same for all subjects. The exact numbers shown to participants are derived from the base numbers in Table 1, using a scaling factor. More precisely, in each period the base numbers shown in Table 1 are multiplied by a scale factor, which is randomly drawn from uniform distribution [100, 200]. This prevents subjects from learning the base numbers. The loans also appear in different order on the screen to avoid learning about the position of each loan.

2.1 Treatments

There are three main treatments: SIMPLE, COMPLEX COST and COMPLEX BENEFIT. In SIMPLE both the benefit and the cost for each option consists of a single number. Figure 1 displays a sample screen for the choice in SIMPLE.[6]

In COMPLEX COST the benefit of each option is a single number as in SIMPLE, while the cost

[5]This does not mean that choices in the field for high-benefit products, but with high costs, are necessarily a mistake. However, controlling for payoffs and choice sets, they are in our experiment.

[6]See Online Appendix A for the instructions and an example screen-shot for the cost choice in SIMPLE.

Loan	Value
Loan A	7300
Loan B	6700
Loan C	6100

Please make a choice among the above 3 Loans. In the 2nd stage you will have to make a choice between 3 repayment options. The repayment options you will get depends on the Loan you choose now. Below you can find the details of all the repayment options for each Loan.

Repayment options for Loan A	Payment amount
Repayment X	4900
Repayment Y	4500
Repayment Z	4300
Repayment options for Loan B	**Payment amount**
Repayment X	4500
Repayment Y	4300
Repayment Z	3400
Repayment options for Loan C	**Payment amount**
Repayment X	4300
Repayment Y	3400
Repayment Z	3100

Figure 1: Choices in SIMPLE

for every scheme consists of three items: A standard fee, a percentage amount and a bonus. Figure 2 gives an example of the way in which complex costs are presented to subjects. For example, the cost of Repayment X in Figure 2 is equal to 4600+0.07*7300-1627=3484.

COMPLEX BENEFIT differs from SIMPLE in how benefits are displayed. Each benefit consists of three items: A standard amount, a percentage amount, and a tax. For example, the benefit for choosing option A in Figure 3 equals $11928 + 0.07 * 13440 - 605 = 12264$. The cost in COMPLEX BENEFIT is a single number as in SIMPLE.

Repayment	Payment Details
Repayment X	A standard Fee of 4600, a percentage fee of %7 of the value of the Loan you have chosen minus a bonus of 1627 .
Repayment Y	A standard Fee of 4800, a percentage fee of %5 of the value of the Loan you have chosen minus a bonus of 2005 .
Repayment Z	A standard Fee of 4700, a percentage fee of %3 of the value of the Loan you have chosen minus a bonus of 583 .

Figure 2: Choices in COMPLEX COST

To examine whether individuals' choices remain the same when there is heterogeneity in the

Loan	Details for the Value of the Loan
Loan A	A standard amount of 11928, plus a percentage amount of %7 of 13440 minus a tax of 605 .
Loan B	A standard amount of 11760, plus a percentage amount of %5 of 12432 minus a tax of 1126 .
Loan C	A standard amount of 12096, plus a percentage amount of %3 of 9408 minus a tax of 2130 .

Figure 3: Choices in COMPLEX BENEFIT

complexity of products, we examine behavior in two additional treatments. First, in treatment ONLY HIGH COMPLEX only the costs for High option are complex, while the costs for Low and Medium options are simple. Next, we examine choices when the costs of both the High and Low options are complex, and the Medium option simple. We use a second treatment, called HIGH & LOW COMPLEX, for this purpose. We focus on heterogeneity in complexity of costs as this is the case that is most closely related to market settings in the field.

The experiment employs a within subject design. In the main type of sessions, A Sessions, subjects play the treatment conditions SIMPLE, COMPLEX COST and COMPLEX BENEFIT four times (or periods) in a randomized order, which is the same for all subjects.[7] In the second type of sessions, B Sessions, subjects play the treatment conditions SIMPLE, COMPLEX COST, ONLY HIGH COMPLEX and HIGH&LOW COMPLEX.[8]

A summary of the treatment conditions by session is presented in Table 2.

		Costs by option		
Treatment	Benefit	High	Medium	Low
A Sessions				
SIMPLE	Simple		All simple	
COMPLEX COSTS	Simple		All complex	
COMPLEX BENEFIT	Complex		All simple	
B Sessions				
SIMPLE	Simple		All simple	
ONLY HIGH COMPLEX	Simple	Complex	Simple	Simple
HIGH & LOW COMPLEX	Simple	Complex	Simple	Complex
COMPLEX COSTS	Simple		All complex	

Table 2: Treatments

[7]To prevent subjects from learning the ranking of the payoffs of the three loans (Medium > High = Low), we introduced 9 "dummy" rounds with different rankings.

[8]In these sessions we aimed to repeat each choice three times. However, due to a programming error the actual number of repetitions turned out to be 3, 3, 2 and 4 for ALL SIMPLE, ONLY HIGH COMPLEX, HIGH & LOW COMPLEX and ALL COMPLEX. Therefore, in the analysis only data from the first two repetitions will be used. However, if we include all repetitions, our results remain qualitatively the same.

Subjects have 120 seconds in the first stage, to choose among different options, and 60 seconds in the second stage, to choose among the costs of the chosen option. Both of these time limits are binding. If subjects fail to make a decision at any stage, they receive 0 points for that period. We chose to implement time limits in order to provide subjects with an implicit cost of decision time. An alternative option would have been to include a price to be paid the longer the subject took to make her decisions. This however introduces an additional level of complexity in the experiment, optimal decision times, which we want to avoid.[9] Also, subjects were not allowed to proceed to the next stage before the time ends. This prevents subjects from trying to finish the experiment sooner.

2.2 Procedures

The experiment was run at Tilburg University (TU) and the University of Queensland (UQ). In total, 184 subjects participated in the experiment. There were 63 participats in A sessions (35 at TU and 28 at UQ), 60 participants in B sessions (32 in TU and 28 in UQ), as well as 51 participants at UQ in a new treatment, described in Section 5. We do not find significant differences in choices across the two locations of the experiment (Mann-Whitney test, p-value>0.15).[10] We hence pool the observations in the results below.

The experiment was programmed and conducted with the software zTree (Fischbacher, 2007). Subjects were recruited through e-mail lists of students interested in participating in experiments. Upon arrival participants were randomly seated behind computers. Subjects had a calculator, pencil and paper available. The instructions were displayed on their computer screen and read aloud by the experimenter. The experiment started when all subjects indicated that they had read and understood the instructions. Earnings were denoted in points and transferred to cash at a rate of 7000 points = 1 EUR in TU and 3200 points =1 AUD in UQ.[11]

The experimental sessions lasted about 75 minutes and subjects on average earned 15 Euros at TU and 32 AUD at UQ. At the end of the experiment a short questionnaire was run.

[9] Note that, in an experiment on search processes where complexity is also manipulated, Caplin et al. (2011) find their results to be robust to the use of time limits.

[10] We provide detailed results by location in Online Appendix B.

[11] In terms of the base parameters, on average 47 points are equal to 1 EUR and 21.5 points are equal to 1 AUD. The exchange rate across locations was adapted to satisfy the expected average payment by hour in each location.

3 Hypotheses

As null hypothesis we assume that consumers make random mistakes when evaluating the payoff of each option, and that these may become more frequent with increased complexity, in line with Carlin (2009). For this reason, we use the random utility model of Luce (1959). According to this model, an individual's utility is the sum of a deterministic component, the net payoff of each option in this case, plus a random utility component. Hence, the utility of choosing option j, where $j = L, M, H$ and the letters L, M and H refer to the Low, Medium and High options respectively, is $u_j = v_j + \epsilon_j$.

In our decision problem we define v_j as the net payoff of the option, its benefit minus the minimum cost of this option. If the error term, ϵ_j, is distributed according to an extreme value distribution with scale factor μ, McFadden (1973) showed that the probability of choosing option j is,

$$Pr[y = j] = \frac{e^{\mu v_j}}{e^{\mu v_L} + e^{\mu v_M} + e^{\mu v_H}} \tag{1}$$

As μ increases, the probability of choosing the option with the highest net payoff increases. Hence, mistakes may occur, especially for small μ values. [12]

We hypothesize that complexity may lead to more mistakes, i.e. decrease the value of μ. This follows from the fact that complexity makes comparing options harder and thus probably makes errors play a larger role. In our main treatments, in the A sessions, we compare COMPLEX BENEFIT and COMPLEX COST. In COMPLEX BENEFIT one item per option is complex, the option's benefit. In contrast, in COMPLEX COST three items per option, the costs, are complex. Hence, we hypothesize that COMPLEX COST is more complex than COMPLEX BENEFIT and this leads to more mistakes. In B sessions, complexity is gradually introduced by increasing the number of options with complex costs. There are none in ALL SIMPLE, one (the High option) in ONLY HIGH COMPLEX, two (the High and Low options) in HIGH & LOW COMPLEX, and three (all options) in ALL COMPLEX. We hence hypothesize that mistakes will be increasing across these treatments. This is summarized in Hypotheses 1A and 1B.

Hypothesis 1A*: Mistakes are more frequent in COMPLEX COST than in COMPLEX BENEFIT and, in both treatments, more frequent than in SIMPLE.*

[12] Our approach is related to the concept of Quantal Response Equilibrium (McKelvey and Palfrey, 1995). We consider an individual decision problem, while they consider a game theoretic setting. A comprehensive overview of the econometric estimation of different error models for individual decision problems can be found in Blavatskyy and Pogrebna (2010).

Hypothesis 1B*: Mistakes increase when the number of options with complex costs increases.*

Interestingly, since the net payoff of the Low and the High option are the same, the random utility model predicts that mistakes will be 'symmetric': If the frequency of mistakes increases, it should increase equally for the High and Low option. This yields Hypothesis 2.

Hypothesis 2*: If mistakes increase, the increase will be equally directed towards the High and Low option.*

Note that Hypothesis 2 makes the strong assumption that mistakes are proportional to the net payoff of each option. However, it may be that complexity in costs makes subjects pay less attention to these choices and focus on simpler and more salient dimensions, as in Chetty et al. (2009). This would lead to more choices of High in COMPLEX COST than in COMPLEX BENEFIT.

Note that although mistakes may display a particular pattern when all costs are complex (A Sessions), heterogeneity in complexity may reverse this result. In ONLY HIGH COMPLEX, both the Medium and the Low option are simple. If individuals display a dislike for complex options, as they do for complex lotteries (Huck and Weizsäcker, 1999), we would expect the Medium and Low to have a 'premium' and be chosen more often.

If complexity makes comparing options harder, its effect could also be observed in decision times (Wilcox, 1993). In line with Hypothesis 1A, in A Sessions, we hypothesize that complexity will lead to the longest decision times in COMPLEX COST, and will also make decision times longer in COMPLEX BENEFIT than in SIMPLE. This leads to Hypothesis 3A. Similarly, in B Sessions, as the number of complex options increases we hypothesize that decision times will increase. This is reflected in Hypothesis 3B.

Hypothesis 3A*: Decision times for choosing among options will be longer in COMPLEX COST than in COMPLEX BENEFIT and, in both treatments, longer than in SIMPLE.*

Hypothesis 3B: *Decision times for choosing among options will increase with the number of options with complex costs, from SIMPLE to ONLY HIGH COMPLEX, and subsequently to HIGH & LOW COMPLEX, and COMPLEX COST.*

4 Results

In this section we present the results from the experiment. Observations where the subjects fail to make a decision on time are dropped from the analysis. These are very few cases, as reported below. Treatment effects are examined with a Wilcoxon matched-pairs signed-rank test using each subject's average score over all repetitions as the unit of observation, unless indicated otherwise. Reported p-values in parenthesis are based on two sided tests, unless otherwise noted.

4.1 Choices

4.1.1 Product choices

Figure 4 shows the average choice frequency with which each option is chosen, High, Medium and Low, in each treatment in A sessions. The first block is for SIMPLE, the second block is for COMPLEX COST and the third block is for the COMPLEX BENEFIT treatment.

In SIMPLE subjects make the optimal choice in a majority of the cases. As shown in the first block of Figure 4, the Medium option is chosen 84% of the time. High is chosen 11% of the time, while Low is chosen about 6% of the time. In line with Hypothesis 1A, as more complexity is introduced, the rate of mistakes increases. The Medium option is chosen least often in COMPLEX COST (46%), significantly less than in SIMPLE (p-value<0.01) and in COMPLEX BENEFIT (p-value<0.01). Also, the Medium option is chosen less frequently in COMPLEX BENEFIT (67%) than in SIMPLE (p-value<0.01).

The increase in mistakes is directed more strongly toward the High option than the Low option in COMPLEX COST. The increase in High, from 11% to 39%, is significantly stronger than the increase in Low, from 6% to 15% of the time (p-value<0.01). Hence, in contrast to Hypothesis 2, subjects in COMPLEX COST exhibit a stronger bias toward the High option.[13]

In COMPLEX BENEFIT we observe as well an increase in the choice frequency of the High option by 12%-points, from 11% to 23%. The increase in the choice frequency of the Low option is of 4%-points, from 6% to 10%. In this treatment, the difference in the increases (12% vs. 4%)

[13] The relative bias towards the High option in the COMPLEX COST treatment is qualitatively the same and yields the same test results with the sample of subjects at Tilburg University than with the sample of students at the University of Queensland. The bias also remains robust over the course of four repetitions. If we consider the first repetition, COMPLEX COST increases the average choice frequency of the High option from 27% in SIMPLE to 58%, while it does not increase the choice frequency of the Low option: it is 10% in SIMPLE and 8% in COMPLEX COST. Similarly, in the last repetition, the average choice frequency of the High option increases from 5% in SIMPLE to 24% in COMPLEX COST, while the increase in the Low option is from 2% in SIMPLE to 17% in COMPLEX COST.

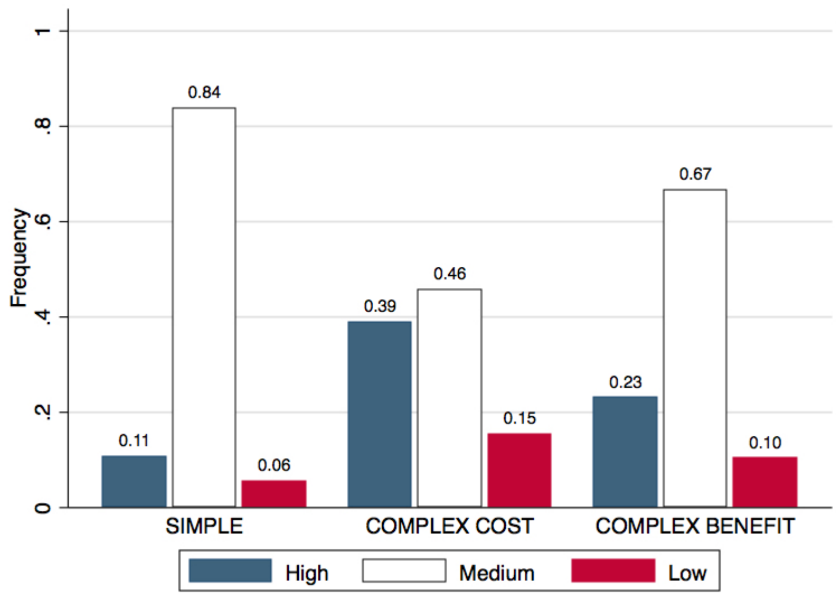

Figure 4: Choices by treatment in A Sessions

is not statistically significant (p-value=0.16). Hence, when benefits are complex, the increase in mistakes is not differentially directed toward the High option, in line with Hypothesis 2.[14]

Results remain qualitatively similar when heterogeneity in the complexity of costs is introduced. Figure 5 shows the average choice frequencies by treatment in B Sessions. The medium option is chosen most often in ALL SIMPLE, 92% of the time. This frequency is higher than that in all other treatments (p-value<0.01 in all cases). Interestingly, the decrease in the frequency with which Medium is chosen is not monotonic. The difference in choices of Medium between ONLY HIGH COMPLEX (74%) and HIGH & LOW COMPLEX (78%) is not significant (p-value=0.16, one-sided). However, when all costs are complex, as in COMPLEX COST, this frequency significantly drops, to 45% (p-value<0.01 in both cases). Hence, once complexity in costs is introduced, mistakes increase, but having one or two options with complex costs does not affect mistakes significantly.

As the number of options with complex costs increases, we observe an increase in the choice of High, which is relatively stronger than that of Low. Comparing SIMPLE to ONLY HIGH COMPLEX, the increase in High –from 4% to 22%– is significantly stronger than that in Low, which is chosen 4% of the times in both treatments (p-value<0.01). If we do the same comparison for HIGH & LOW COMPLEX, we find similar results. The increase in High is stronger than that in Low, compared to SIMPLE. Though in this case, the difference is not significant (p-value=0.15).

[14] Further, the increase in the choice of High is higher in COMPLEX COST compared to SIMPLE, than in COMPLEX BENEFIT (p-value<0.01).

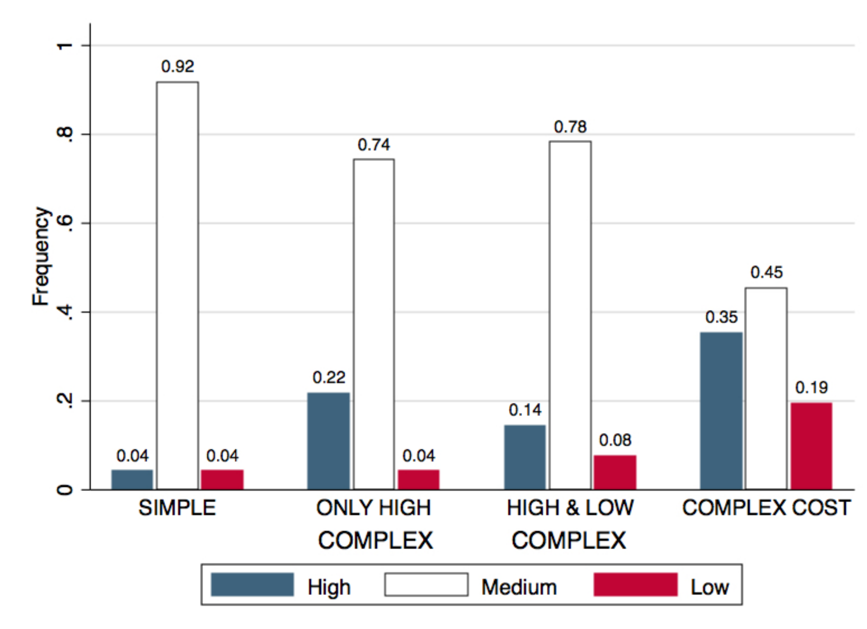

Figure 5: Choices by treatment in B Sessions

Finally, in COMPLEX COST the increase in High, from 4% to 35%, is stronger than that in Low, from 4% to 19% (p-value=0.07).

The results are confirmed in multinomial regressions of the determinants of choices (see Section B.2 of the Online Appendix). In these regressions we allow for a time trend and we control for gender, age and location. We find that choices of High decrease over time (significant) and that men make less High choices in the A sessions (marginally significant). We find no significant effect of location or age.

Our findings indicate that complexity increases mistakes, and these are most frequent in COMPLEX COST, in line with Hypothesis 1A and 1B. However, individuals in this treatment do not display a "symmetric" increase in mistakes, but a strong tendency to choose the High option, especially in COMPLEX COST, relative to COMPLEX BENEFIT. This leads to Results 1 and 2.

Result 1*: Mistakes increase when complexity is introduced, and these are most frequent in COMPLEX COST, in line with Hypothesis 1A. Mistakes also (weakly) increase as an increasing number of costs become complex, in line with Hypothesis 1B.*

Result 2*: Mistakes do not increase equally toward the High and Low option. They display a significantly stronger tendency towards High, especially in COMPLEX COST. Hence, we reject*

Hypothesis 2.

4.1.2 Cost choices

We briefly examine subjects' cost choices. In A sessions, after having chosen a particular option, subjects most frequently choose the lowest cost, especially in SIMPLE (97% of the cases) and COMPLEX BENEFIT (96% of the cases). In contrast, in COMPLEX COST they more often make mistakes. Subjects choose the lowest cost in 68% of the cases. This frequency is significantly different to that in SIMPLE and COMPLEX BENEFIT (p-value<0.01 in both cases). Interestingly, an overwhelming majority of the mistakes made in the cost choices are made by subjects who chose the High option. Of 78 cases in which subjects do not choose the lowest cost in COMPLEX COST, 53 of them are cases where the option chosen is High, 17 where it is Medium and 8 where it is Low.

Cost choices in B sessions are similar to those in A sessions. In the treatment SIMPLE, the lowest cost is chosen in 97% of the cases. Subjects choose the lowest cost in 84% of the cases in ONLY HIGH COMPLEX and in 92% of the cases in HIGH & LOW COMPLEX.[15] In the treatment COMPLEX COSTS, subjects choose the lowest cost in 65%. In this case, the difference compared to all other treatments is statistically significant (p-value<0.01 in all cases). Again, in this treatment, those making mistakes in their cost choices are most frequently subjects who chose the High option in the first place.

4.2 Decision time

Complexity not only leads to different choices, but also to longer decision times. Table 4 displays decision times, by treatment in A and B sessions. Most subjects in SIMPLE make their choice in 20 to 60 seconds. In contrast, a majority of subjects need more than 100 seconds to make their choice in COMPLEX COST. Similarly, a majority of subjects need more than 80 seconds in COMPLEX BENEFIT. Average decision time in SIMPLE (57.3 secs.) are significantly different from those in COMPLEX COST (92.6 secs., p-value<0.01) and COMPLEX BENEFIT (90.0 secs., p-value<0.01), as predicted in Hypothesis 3A. There is also a weakly significant difference in decision times between COMPLEX COST and COMPLEX BENEFIT (p-value=0.09, one-sided).[16]

Introducing even only a little complexity (in one option) increases decision times significantly. On average, in B sessions, decision time among options is 55.5 seconds in SIMPLE, and it jumps

[15] The difference is significant (p-value=0.03).

[16] A regression analysis of decision times, taking into account censoring, is provided in the Online Appendix. Results are qualitatively the same as those reported in the main text using simple tests.

to over 87 seconds in all other treatments (89.6, 87.3 and 95.8 in ONLY HIGH COMPLEX, HIGH & LOW COMPLEX, COMPLEX COST). The percentage of choices in the last seconds, 100 to 120, is 42.5% and 49.6% in ONLY HIGH COMPLEX and HIGH & LOW COMPLEX, only slightly below that in COMPLEX COST in B sessions (63.9%). On average, the difference in decision times between SIMPLE and ONLY HIGH COMPLEX is significant (p-value<0.01). However, comparing ONLY HIGH COMPLEX and HIGH & LOW COMPLEX we find no significant difference (p-value=0.28, one-sided). Decision times increase significantly between HIGH & LOW COMPLEX and COMPLEX COST (p-value=0.01).[17] It is interesting that, as in the case of mistakes, decision time does not change if one rather than two options display complex cost schemes.

Session		*A Session*			*B Session*		
Treatment	SIMPLE	COMPLEX COST	COMPLEX BENEFIT	SIMPLE	COMPLEX COST	ONLY HIGH COMPLEX	HIGH & LOW COMPLEX
Distribution of decision time (in seconds)							
Choice among options							
<20	4.4%	2.0%	2.0%	0.8%	4.2%	2.5%	1.7%
20-40	25.0%	4.5%	3.2%	25.8%	5.9%	5.0%	1.7%
40-60	31.0%	7.3%	8.7%	37.5%	10.1%	6.7%	11.7%
60-80	18.3%	10.9%	15.1%	24.2%	12.6%	5.9%	14.2%
80-100	15.1%	20.6%	30.2%	7.5%	17.6%	16.0%	28.3%
>100	6.3%	54.7%	40.9%	4.2%	49.6%	63.9%	42.5%
Choice among costs							
<20	92.1%	25.5%	92.1%	93.3%	26.9%	66.7%	78.2%
20-40	6.0%	27.5%	6.0%	5.8%	19.3%	14.2%	5.9%
40-60	2.0%	47.0%	2.0%	0.8%	53.8%	19.2%	16.0%
% of No Choice							
Among options	0.0%	2.0%	0.0%	0.0%	0.8%	0.0%	0.8%
Among costs	0.0%	1.2%	0.0%	0.0%	0.8%	0.0%	0.0%

Table 3: Decision time, by treatment and session

Choosing among the different costs also takes longest in COMPLEX COST, where subjects frequently need 40 to 60 seconds (47.0% and 53.8% of the time). This is in stark contrast to decision times in all other treatments. In A sessions, the differences in decision times are significant (COMPLEX COST compared to SIMPLE, p-value<0.01, and compared to COMPLEX BENEFIT, p-value<0.01). In B sessions, decision times increase significantly from SIMPLE to ONLY

[17] We note that there is a small non-significant difference in decision times across locations in HIGH & LOW COMPLEX. Subjects in Tilburg University spend on average 91.8 secs. choosing among options, while subjects at the University of Queensland spend on average 82.1 secs. This leads to a significant increase in decision times when moving to COMPLEX COST in the latter location, but not in the former. Further details are provided in Online Appendix B.

HIGH COMPLEX (p-value<0.01), further increase from ONLY HIGH COMPLEX to HIGH & LOW COMPLEX (p-value<0.01), and then increase again from HIGH & LOW COMPLEX to COMPLEX COST (p-value<0.01).

Result 3*: Decision times increase significantly with complexity from in SIMPLE to COMPLEX BENEFIT and weakly increase to COMPLEX COST in line with Hypothesis 3A. However, change in decision times is not monotone in the number of complex options in B Sessions. Thus, we reject Hypothesis 3B.*

Overall, although choices took longer when complexity was introduced, subjects rarely ran out of time, as reported in the bottom part of Table 4 and 5. In A sessions, this only happened in COMPLEX COST: in 2.0% of the cases when choosing among options and in 1.2% of the cases when choosing among costs. In B sessions, only in two occasions subjects ran out of time choosing among options, when at least two options had complex costs. Only once a subject ran out of time when choosing among costs, in COMPLEX COST.

4.3 Payoffs

The consequences of complexity are reflected in payoffs.[18] Since the Medium option offers the highest maximum payoff, it follows naturally that complexity leads to lower payoffs. In A sessions we find that subjects earn 28.7 points in COMPLEX COST, while they earn 32.2 points in SIMPLE and 31.8 points in COMPLEX BENEFIT. The difference in profits between COMPLEX COST and SIMPLE, as well as COMPLEX BENEFIT is significant (p-value<0.01 in both cases). Overall, complexity in costs leads to significantly lower efficiency levels, as measured by the ratio of average payoffs to maximum payoffs. When costs are complex efficiency is 87%, while it is 98% when all options are simple or 96% when benefits are complex.

In B sessions we obtain a very similar result. Profits in COMPLEX COST are 28.9 points, while they are 32.5 points in SIMPLE. The difference is significant (p-value<0.01). Profits when only one or two options are complex lie in between. In ONLY HIGH COMPLEX subjects earn 31.4 points, while in HIGH & LOW COMPLEX they earn 31.6 points. The difference between these treatments is not significant (p-value=0.11). Hence, complexity in costs, especially when all options are complex, leads to lower efficiency levels (87%).

[18] In the analysis of payoffs we include all periods, including the few instances in which subjects did not make a choice within the time limit. Results remain qualitatively the same if these periods are excluded.

5 Salience versus narrow bracketing

The experimental evidence reveals that, when costs are complex, there is a strong increase in choices of the high-benefit option relative to the low-benefit option. We also find the bias towards the high-benefit option to persist when only the high benefit option or both the high and the low-benefit options have complex costs. However, we do not find a significant bias towards neither the high nor the low benefit option when benefits are complex. We discuss two potential explanations for these results, salience and narrow bracketing, and provide additional experimental evidence suggesting that salience is the main force behind the results.

A potential explanation for our findings is that complexity affects the 'salience' of certain attributes of an option. We consider an attribute to be salient if it is presented in a relatively simple manner. For example, both Bordalo et al. (2013) and Köszegi and Szeidl (2013) suggest that the simple dimension of a product receives more attention. In COMPLEX COST this would imply that benefit is salient and hence subjects would choose High. This is in line with the increase in High choices we observe. Similarly, as the complexity of the benefits increase from SIMPLE to HIGH COMPLEX to HIGH & LOW COMPLEX to COMPLEX COST the saliency and hence the choice frequency of the High option (weakly) increases. How saliency applies to COMPLEX BENEFIT is less clear. One interpretation is that, in COMPLEX BENEFIT costs are simpler, and hence more salient. Thus, subjects should pay more attention to the cost dimension. This would imply that subjects choose the Low option more frequently in this treatment. However, in our experiment, each option has a lowest cost, which is easy to find. Once subjects have seen these costs, they need to consider the benefits of each option. Since all options have complex benefits, none of these is salient. This would suggest that subjects would choose randomly across the three options, in line with the data.

An alternative explanation for our findings is narrow bracketing. Narrow bracketing implies making choices in isolation, while broad bracketing refers to integrating the consequences of multiple choices (Read et al., 1999). In the setup of our experiment, narrow bracketing could be interpreted as disregarding the future choice among costs. This would lead to choosing High, which offers the highest benefit. In contrast, broad bracketing would imply taking the future choice among costs into account at the moment of choosing an option. This would result in choosing the Medium option, which offers the highest net payoff. While narrow bracketing is easier than broad bracketing in most situations, relative ease of these two ways of bracketing may depend on the complexity of the decision problem. Narrow bracketing can be argued to be cognitively easy in COMPLEX COST - only focus on simple benefit-, while broad bracketing is demanding - focus on simple benefit and complex cost. This could explain the strong tendency to choose the High option, relative to the Low option, in this treatment. In contrast, in COMPLEX BENEFIT, narrow bracketing is not cognitively easier than broad bracketing, since costs are simple. This could at the same time explain why individuals do not display the strong tendency to choosing High in this treatment.

A central difference between the two explanations is that narrow bracketing assumes that individuals make choices sequentially, especially when costs are complex. The timing of choices under salience is not relevant. To test these alternative explanations, we designed a new treatment in which subjects chose the product and its cost simultaneously, i.e. they made both choices on the same screen. Under simultaneous choices, it is more difficult to bracket narrowly. Hence, if narrow bracketing is the explanation for our results, subjects should choose High less often when choices are simultaneous, compared to when they are sequential, especially in COMPLEX COST. By contrast, if salience is the explanation for our results, choices should not be affected by the simultaneity of choices.[19] Figure 6 shows the average choice frequency with which each option is chosen, when the choice among options and among costs is made simultaneously.

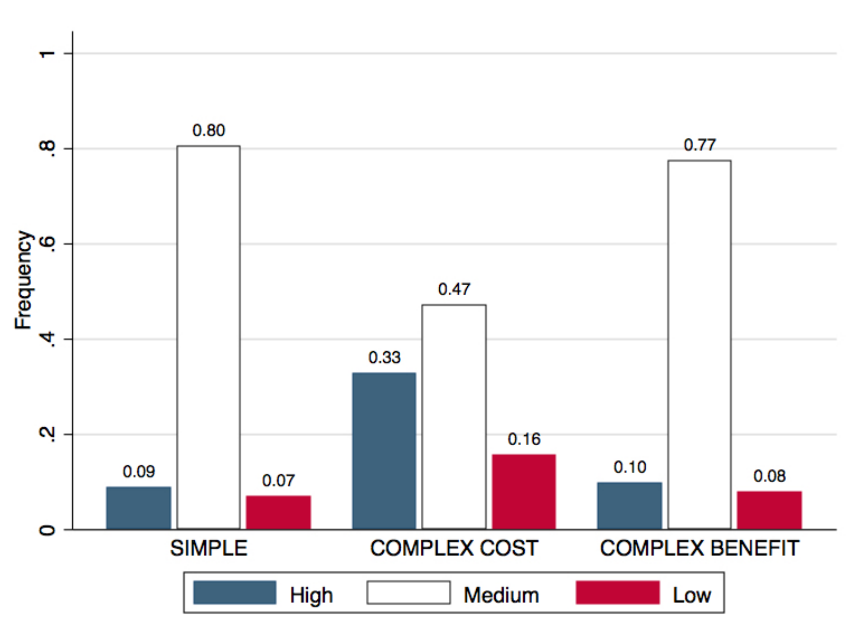

Figure 6: Choices by treatment, when product and cost choices are made simultaneously

Our results reveal that choices are not affected by the simultaneity of choices. Under SIMPLE

[19]We ran two sessions of the simultaneous treatment at the University of Queensland with a total of 51 subjects. These sessions were ran using the same procedure as outlined above.

and COMPLEX COST, we observe no difference in choices, relative to sequential choices, as shown in Figure 4 (Mann-Whitney test, p-value>0.1 in all cases). Hence, our results suggest that salience is the main explanation for our results.

Under COMPLEX BENEFIT, subjects choose High less often (Mann-Whitney test, p-value<0.01), while they choose Medium more often (Mann-Whitney test, p-value=0.02) than in sequential choices. This result is explained by the fact that subjects now had a total of 180 seconds to make their choices. Since costs are simple and can be chosen in less than 20 seconds by a majority of the subjects, this gave them more time to choose among options and hence make better choices.

6 Conclusion

The complexity of products has been highlighted in recent years as a source of mistakes for consumers. In this paper we examine how different types of complexity affect individual choices, in two-step choices where individuals first choose among products and then among their costs. By controlling the exact benefits and costs of a set of available options, we examine whether complexity leads to more mistakes and, more importantly, explore whether different kinds of complexity lead to different kinds of mistakes. This is a crucially important step in order to guide policy makers in regulating the disclosure of information, for example. While complexity could simply lead to more mistakes, it could also lead to specific biases that are particularly harmful for consumers.

Our results reveal that the kind of complexity is crucial. When costs are complex, choices display a strong bias toward the high benefit option. In contrast, when benefits are complex, choices display a weaker bias towards this option, and mistakes are more evenly distributed. Further, when we explore the effects of heterogeneity in the number of complex options, we find that complexity in costs can have similar effects when all options are complex and when only a subset features complex costs.

A central question is, how can the effects of complexity be explained? Our results suggest that individual choices are driven by the salience of the options. Different types of complexity affect which options are salient in different ways. When costs are complex, benefits become more salient and the option with high benefits more attractive. In contrast when benefits are complex, none of the benefits is salient, reducing the bias towards the option with high benefits.

Overall, the results suggest that regulation aimed at consumer protection in complex markets, such as markets for credit and insurance, should take into account what kind of complexity is used by producers, since this is likely to be a key factor in determining what kind of mistakes consumers make.

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